Towards Fully Autonomous Driving ? The Perception & Decision-making bottleneck (Plenary Talk)

Christian Laugier

Towards Fully Autonomous Driving ?
The Perception & Decision-making bottleneck

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ADAS & Autonomous Driving

Plenary Talk
IEEE ARSO 2016, Shanghai, July 7-9 2016

Socio-economic context

- On-going change of the role & concept of private car in human society

Ownership & Feeling of Freedom
Affective behaviors & Social position
Driving pleasure … but less and less true !

*Focus on **Technologies** for*
Safety & Comfort & Reduced Pollution
Driving Assistance v/s Autonomous Driving

- Technology & Internet progressively change de **mobility habits** of people
  => Shared mobility systems, more carpooling, more ADAS …
  e.g. Uber, BlaBlaCar, Tesla Autopilot …

- A Huge ADAS market for Automotive Industry
  *=> **$16 billions** in 2012 & Expected **$261 billions** in 2020* [f]

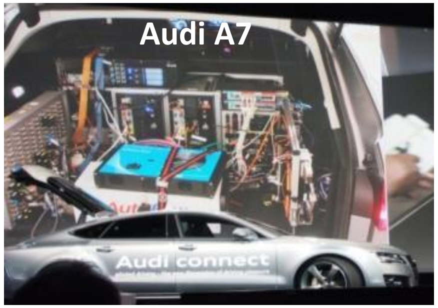
[f] Forecasted US$ 260 Billion Global Market for ADAS Systems by 2020. ABI Research. 2013.

Technological context

- **Perception** for Autonomous Vehicles: *New trend of automotive industry !*
  - ✓ Perception is a bottleneck for Motion Autonomy
  - ✓ Strong improvements (sensors & algorithms) during the last decade

CES 2015 & 2016
(Las Vegas)

- *But… **High Computational requirement & Insufficient Robustness** are still an obstacle to the full deployment !*



Lack of Robustness & Efficiency

Lack of Integration into Embedded Sw/Hw

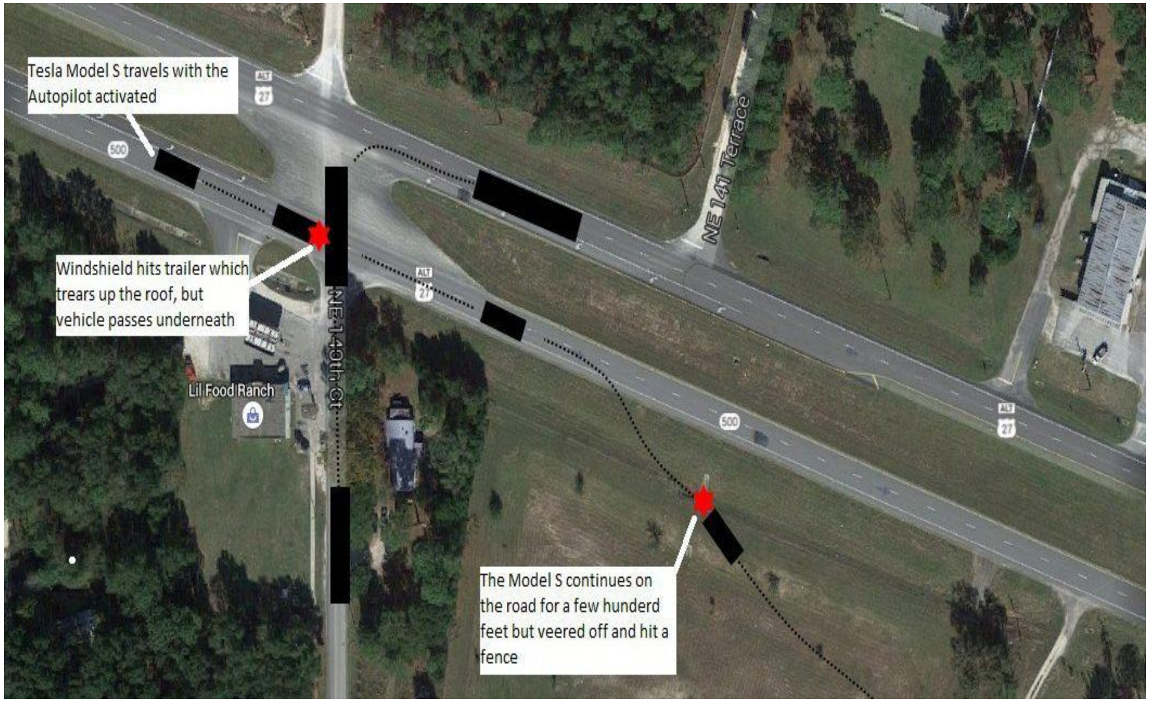
What about Safety issue ?

❑ **Safety is still insufficient** *(a false sense of Safety)* **!**

=> Still some Perception & Situation Awareness errors (even in commercial systems)

=> On May 7th 2016, ***Tesla driver killed*** *in crash with Autopilot active (recently revealed by Tesla)*

Tesla Model S – Autopilot
Front perception:
Camera + Radar + US sensors

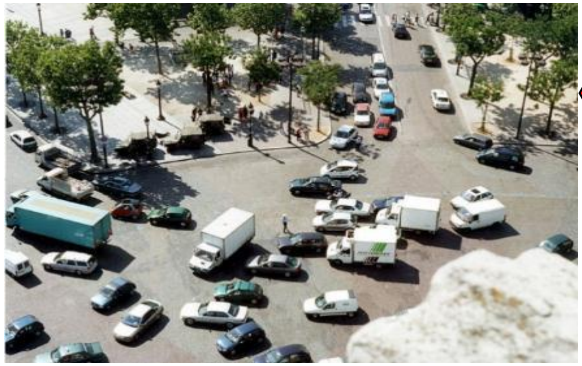


Autopilot didn't detected the trailer as an obstacle *(NHTSA investigation + Tesla conjecture):*

- **Camera** => *White color against a brightly lit sky (+ High ride height ?) !*
- **Radar** => *High ride height of the trailer probably confused the radar into thinking it is an overhead road sign !*

Focus of this talk: *How to improve current Embedded Perception & Decision-making Systems ?*

Complex Dynamic Scenes



Situation Awareness & Decision-making

Road Safety campaign, France 2014

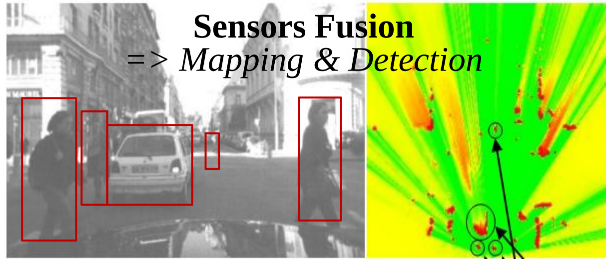
Anticipation & Prediction

Main features

- ✓ Dynamic & Open Environments *(Real-time processing)*
- ✓ Incompleteness & Uncertainty *(Model & Perception)*
- ✓ Human in the loop *(Social & Interaction Constraints)*
- ✓ Hardware / Software integration *(Satisfying Embedded constraints)*

Key Technology 1: Bayesian Perception

Embedded Multi-Sensors Perception
⇒ Continuous monitoring of the dynamic environment



❑ Main difficulties

*Noisy data, Incompleteness, Dynamicity, Discrete measurements + **Real time !***

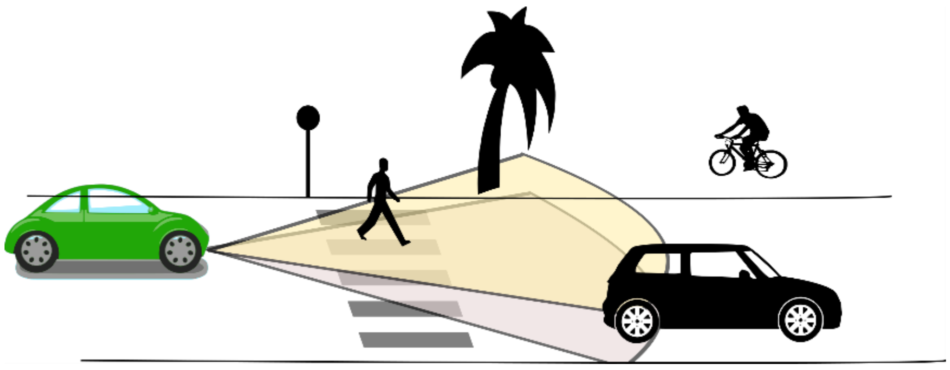
❑ Approach: Bayesian Perception

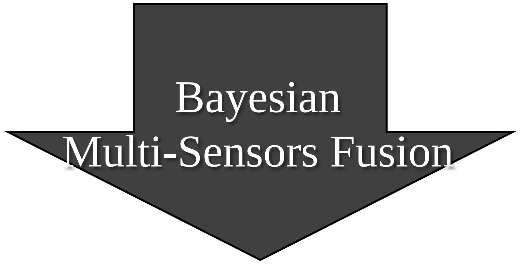
- *Reasoning about **Uncertainty & Time window** (Past & Future events)*
- ***Improving robustness** using **Bayesian Sensors Fusion***
- ***Interpreting the dynamic scene** using **Contextual & Semantic** information*

Bayesian Perception : Basic idea

Multi-Sensors Observations

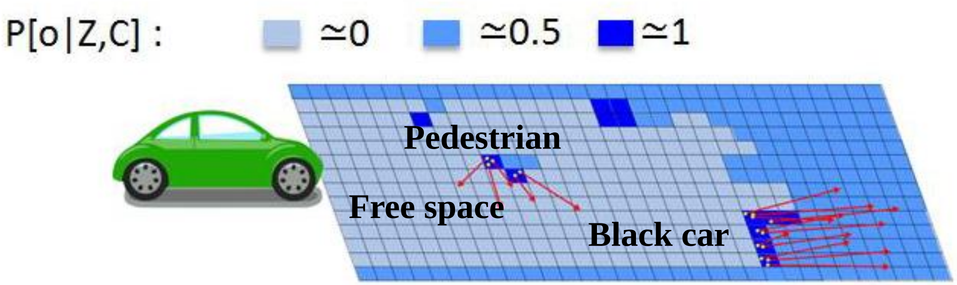
Lidar, Radar, Stereo camera, IMU …





Probabilistic Environment Model

- *Sensor Fusion*
- *Occupancy grid integrating uncertainty*
- *Probabilistic representation of Velocities*
- *Prediction models*

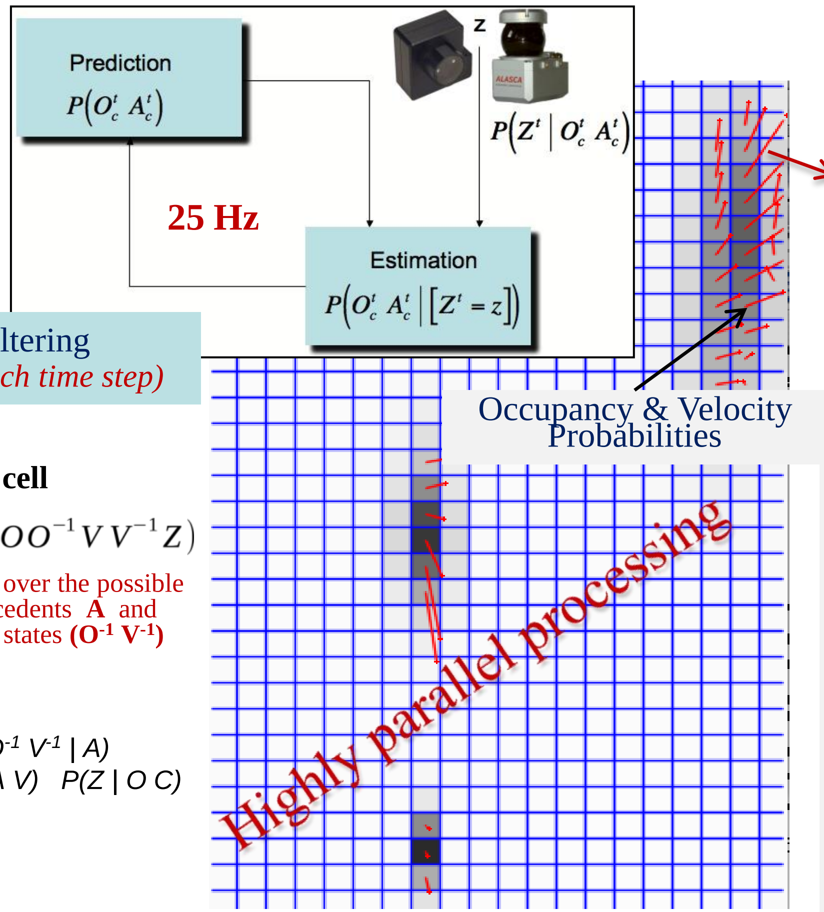


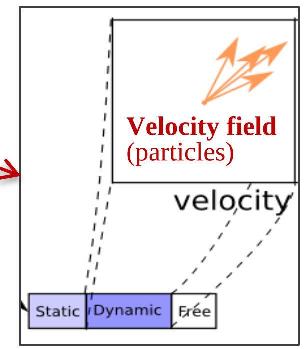
Occupancy probability + Velocity probability
+ Motion prediction model

A new framework: *Dynamic Probabilistic Grids*
A clear distinction between Static & Dynamic & Free components

[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]

Sensing *(Observations)*





Bayesian Filtering
(Grid update at each time step)

Solving for each cell

$$P(O\,V \mid Z\,C) = \lambda \sum_{A\,O^{-1}\,V^{-1}} P(C\,A\,O\,O^{-1}\,V\,V^{-1}\,Z)$$

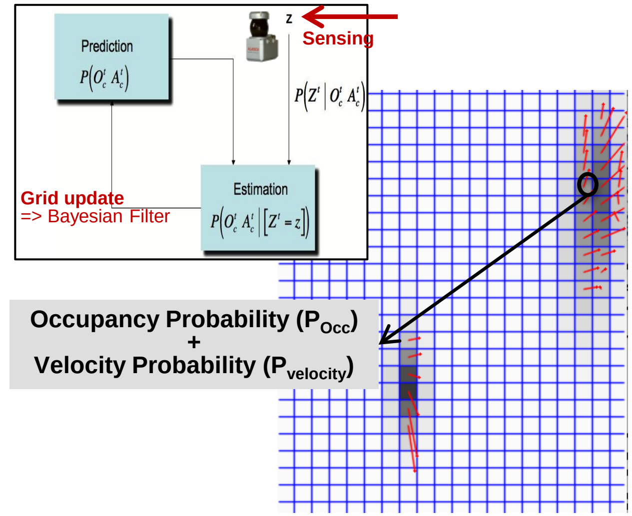
Sum over the possible antecedents **A** and their states **(O^{-1} V^{-1})**

Joint Probability decomposition:

$$P(C\,A\,O\,O^{-1}\,V\,V^{-1}\,Z) = P(A)\ \ P(O^{-1}\,V^{-1} \mid A)\ \ P(O\,V \mid O^{-1}\,V^{-1})\ \ P(C \mid A\,V)\ \ P(Z \mid O\,C)$$

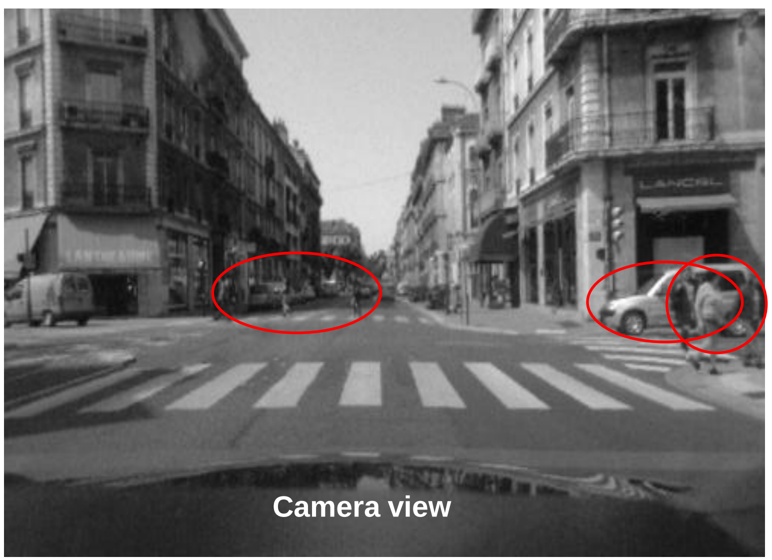
- *Bayesian Occupancy Filter (BOF)*
  => Patented by Inria & Probayes
  => Commercialized by Probayes
  => Robust to sensing errors & occultation
- *Used by: Toyota, Denso, Probayes, IRT Nanoelec / CEA*
- ***Free academic license available***
- ***Industrial license under negotiation with Toyota***

Bayesian Occupancy Filter (BOF) – *Outline*

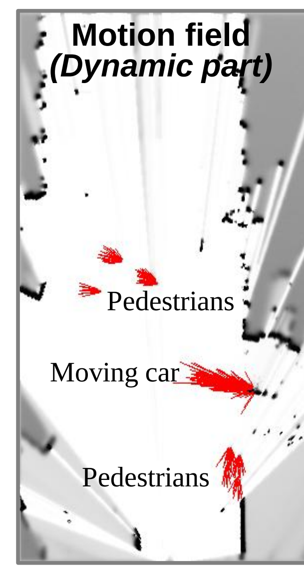


Main features:

- Estimate **Spatial occupancy**
- Analyze **Motion Field** *(using Bayesian filtering)*
- **Reason at the Grid level** *(i.e. no object segmentation at this reasoning level)*

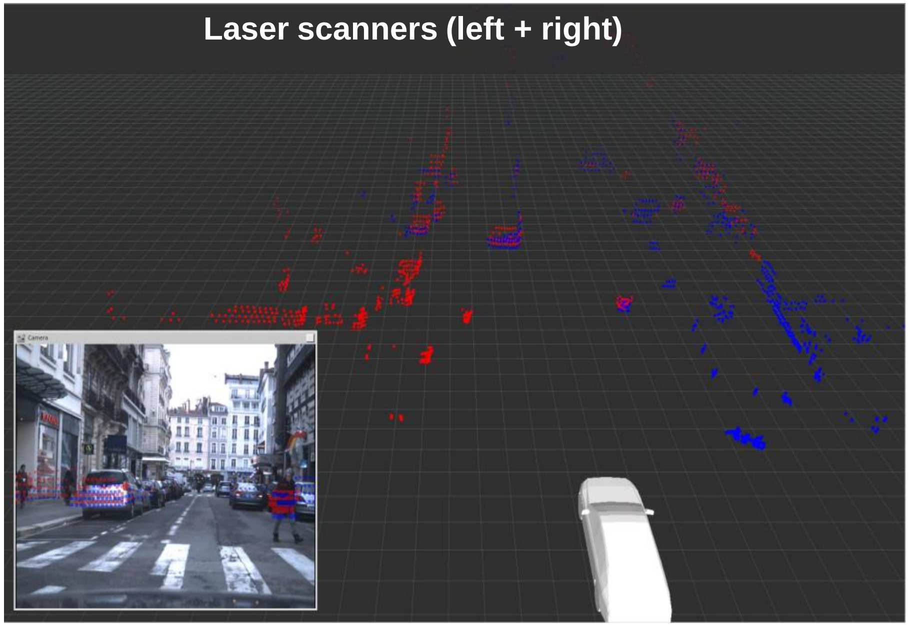


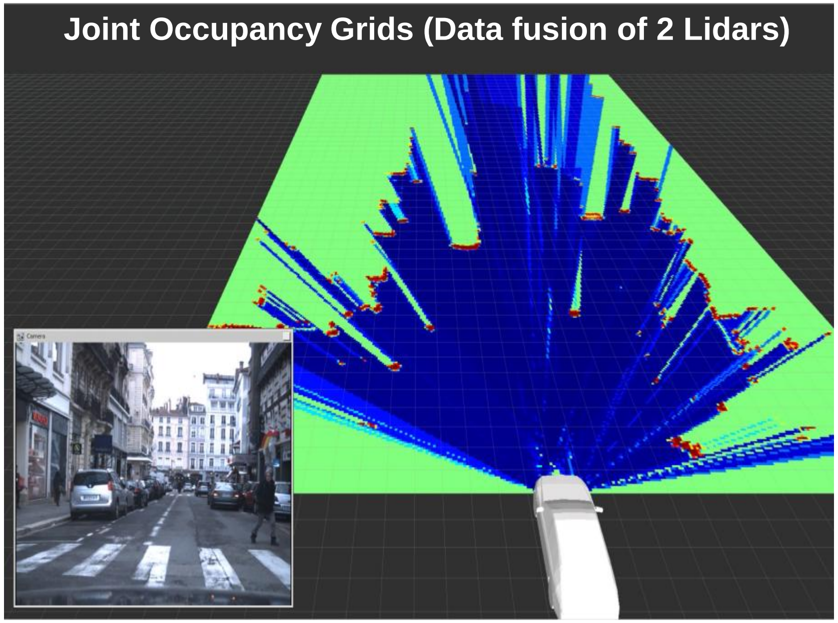
Sensors data fusion
+
Bayesian Filtering



Data fusion: *The joint Occupancy Grid*

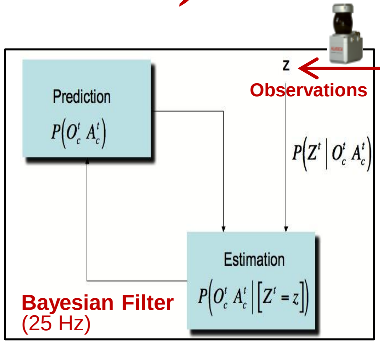
- **Observations Z_i** are given by each sensor ***i*** *(Lidars, cameras, etc)*
- For each set of observation Z_i , **Occupancy Grids are computed:** $P(O \mid Z_i)$
- Individual grids are **merged into a single one:** $P(O \mid Z)$

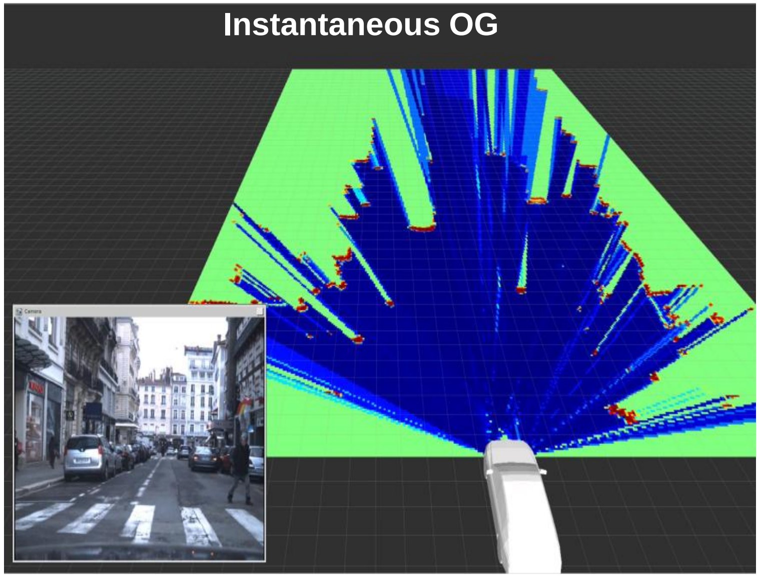


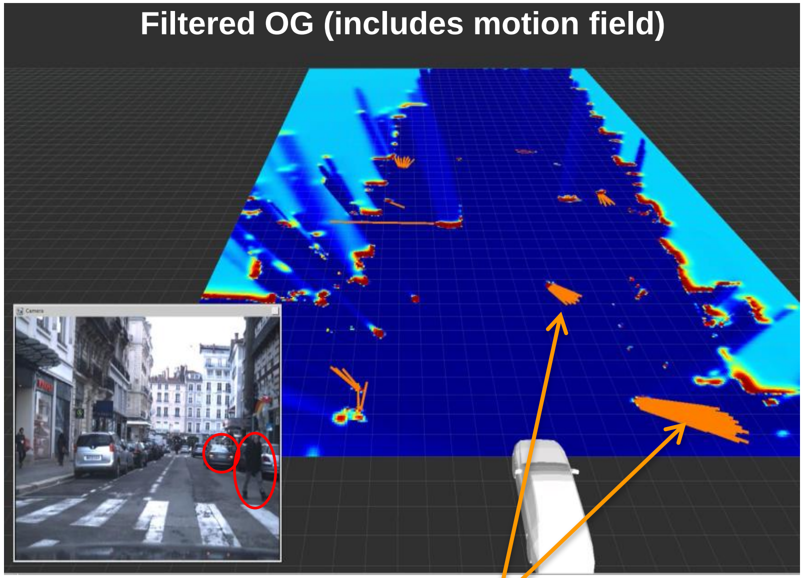


Taking into account dynamicity:
Filtered Occupancy Grid (Bayesian filtering)

- **Filtering** is achieved through the ***prediction/correction loop*** ***(Bayesian Filter)***
  *=> It allows to take into account **grid changes over time***
- **Observations** are used to update the environment model
- **Update is performed in each cell** **in parallel** *(using BOF equations)*
- **Motion field** is constructed from the resulting filtered data







Motion fields are displayed in orange color

Underlying Conservative Prediction Capability

=> Application to Conservative Collision Anticipation

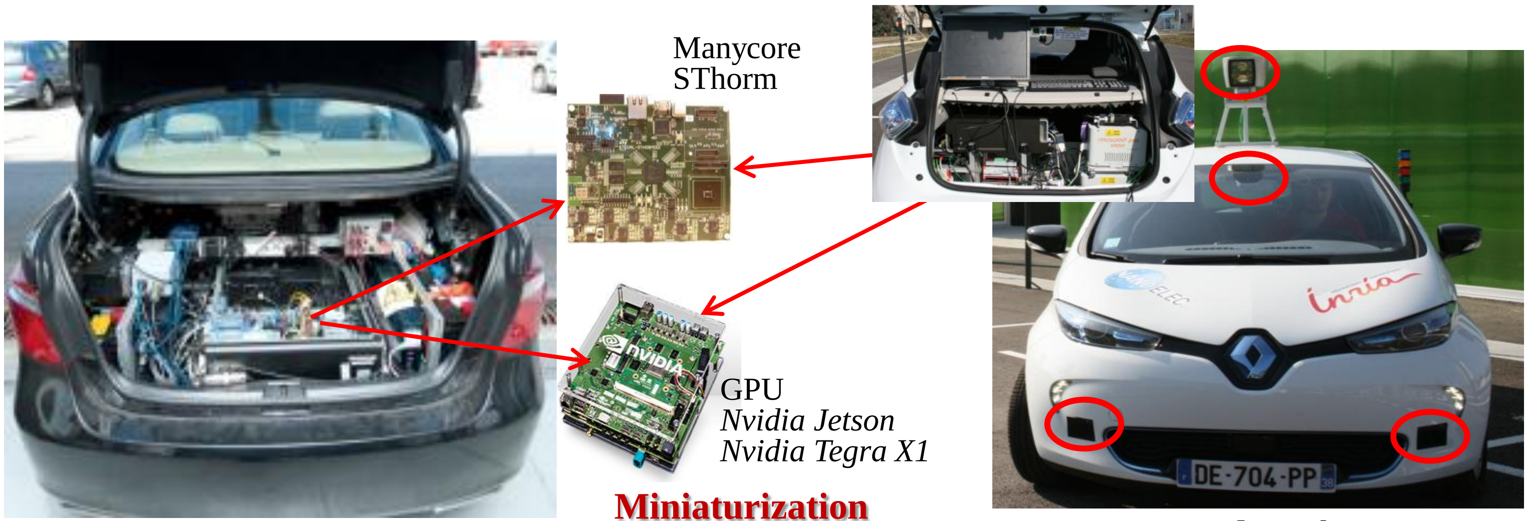
Autonomous Vehicle (Cycab)

Parked Vehicle (occultation)

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle "anticipates" the behavior of the pedestrian and brakes *(even if the pedestrian is temporarily hidden by the parked vehicle)*

Implementation & Experiments (Vehicles)

CPU+GPU+ROS / Stereo vision + Lidars + GPS + IMU + Odometry



Toyota Lexus **Renault Zoé**

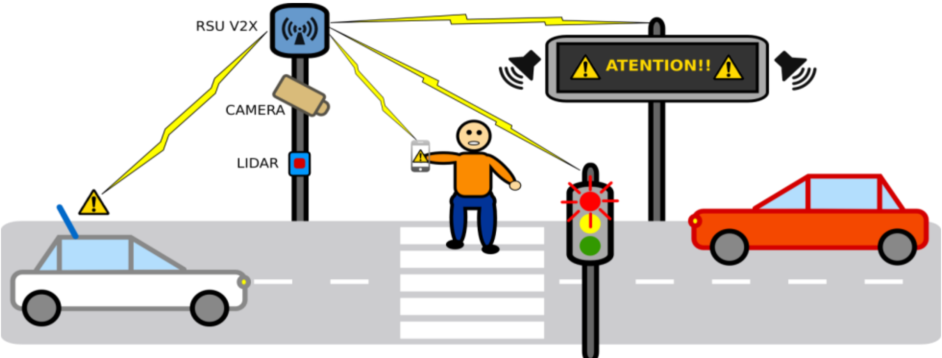
Implementation & Experiments (Infrastructure)

IRT Nanoelec experimental platform => Connected infrastructure + 2 Twizy

Equipped Renault Zoé

Connected & Movable Perception Box

Equipment for pedestrian crash test

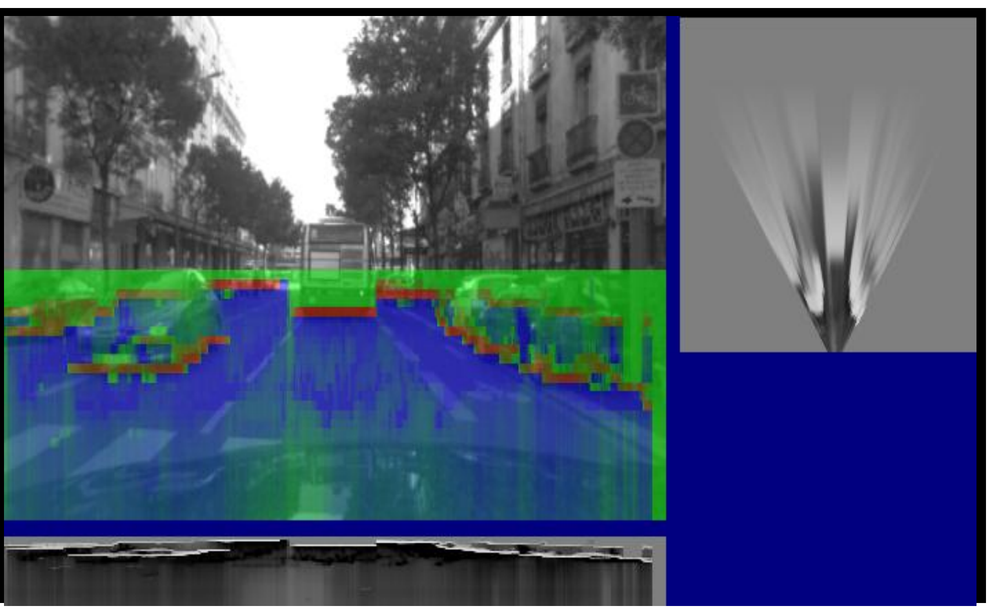


Experimental connected infrastructure

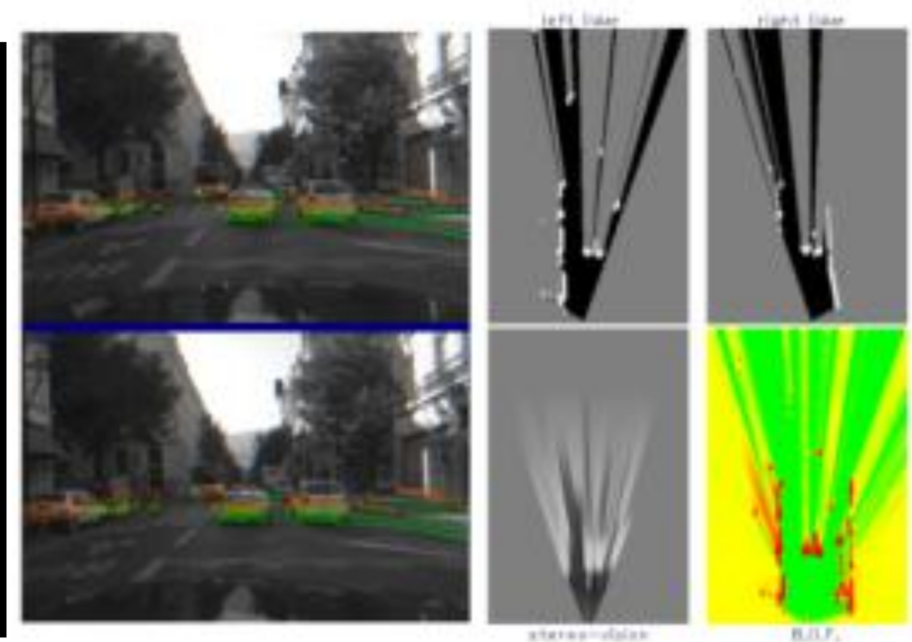
Experimental Results *(Inria – Toyota Lexus)*

Multiple sensors Fusion (Stereo vision & Lidars)

[Perrollaz et al 10] [Laugier et al ITSM 11]
IROS Harashima Award 2012



Stereo Vision
(U-disparity OG + Road / Obstacles classification)



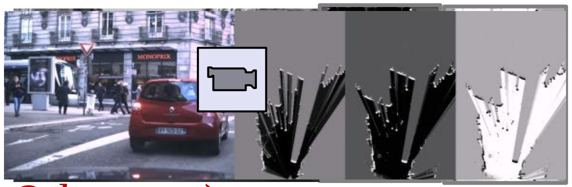
Bayesian Sensor Fusion *(Stereo Vision + Lidars)*

Recent implementations & Improvements

Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity :**

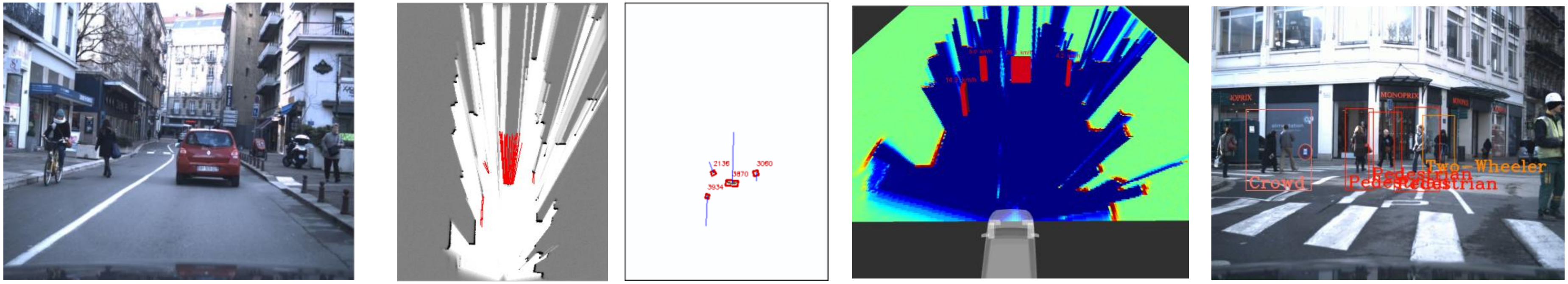
[Negre et al 14] [Rummelhard et al 14]

- Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014)
  - ✓ *Reducing memory size by a factor 100*
  - ✓ *More efficient in complex environments*
  - ✓ *Velocities estimation more accurate*
    => using Particles & Motion data from vehicle (IMU + Odometry)

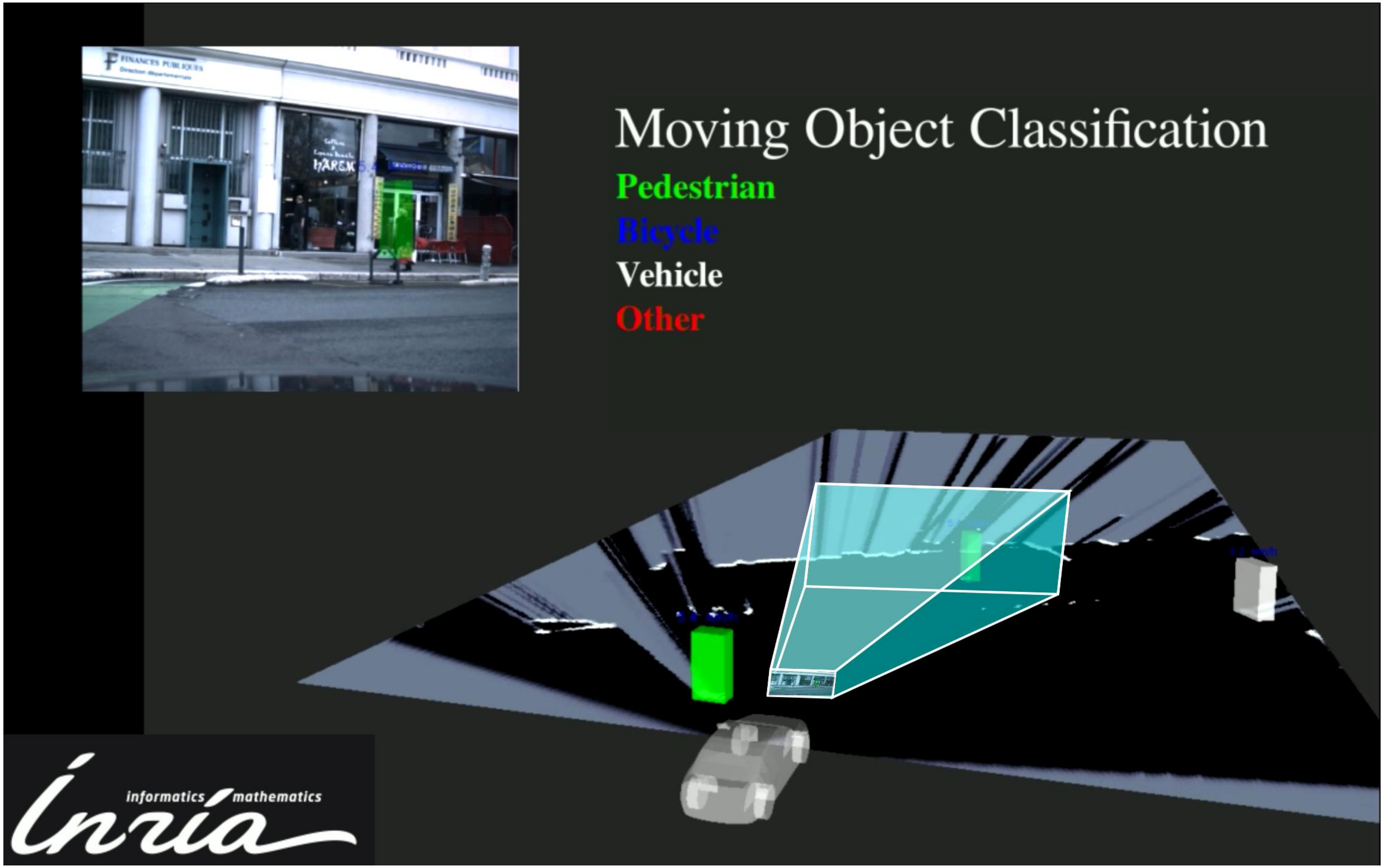


[Rummelhard et al 15]

- Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015)
  - ✓ *Increasing efficiency using "state data" (Static, Dynamic, Empty, Unknown)*
  - ✓ *Incorporating a "Dense Occupancy Tracker" (using particles propagation & ID)*

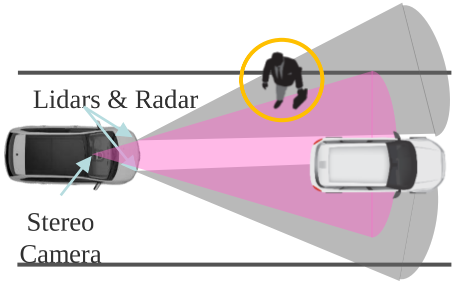


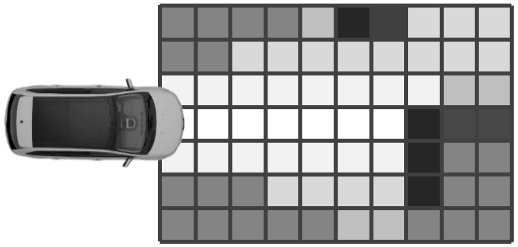
CMCDOT Detection & Tracking results



Software / Hardware Integration – Motivation

PhD Tiana Rakotovao





OGs in practice:
- High number of cells
- Several sensors

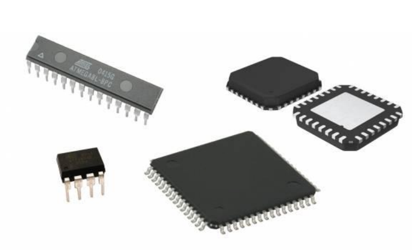
~ Billions Floating-point operations per sec

Hardware accelerators

High-end GPUs & CPUs

Not adapted for automotive industry

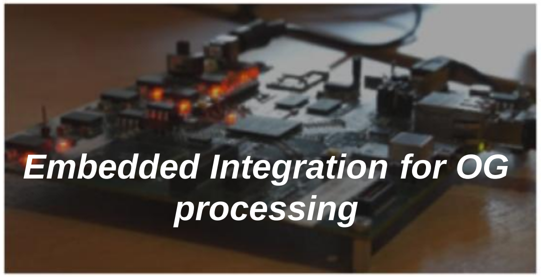
Microcontroller, FPGA

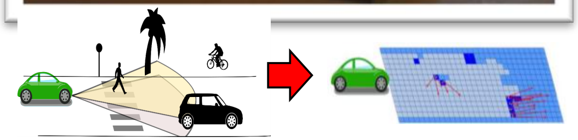


How to integrate **computing requirements** of OGs into embedded ECUs ?

PhD Tiana Rakotovao

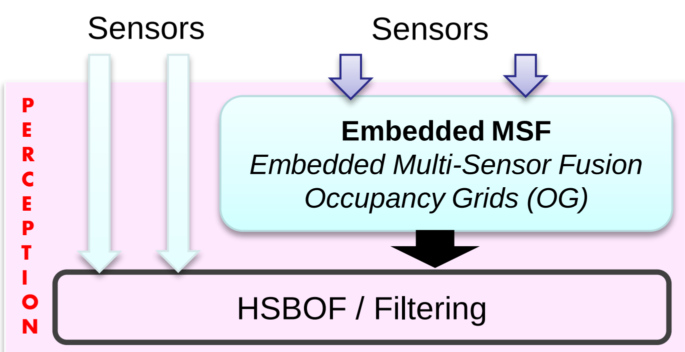
❑ The challenge: *How to cope with contradictory requirements & constraints ?*

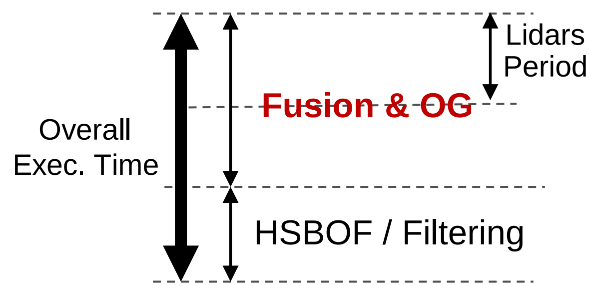




- **Embedded characteristics:** ***Low*** *computing power, Low memory space, Low bandwidth*
- **Embedded constraints:** ***Low*** *purchase cost, Low energy consumption, Small physical size*
- **Algorithmic constraints:** ***High*** *computing requirement,* ***High*** *memory space & bandwidth requirement*

❑ Time Performance Analysis





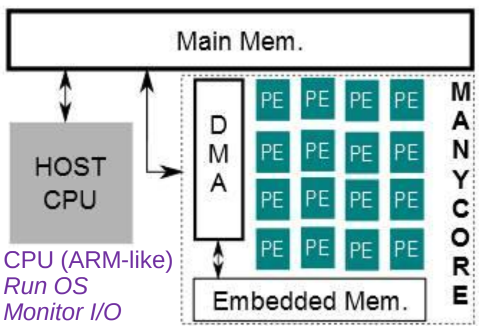
HW Accelerator
=> Focus on
Embedded Multi-Sensor Fusion

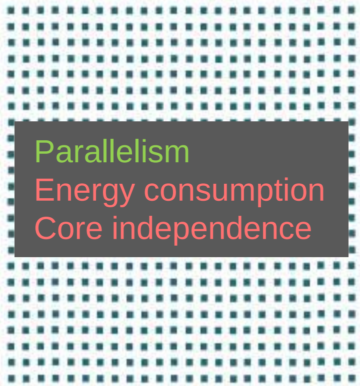
Software / Hardware Integration – Architectures

PhD Tiana Rakotovao

Some Embedded Hardware characteristics

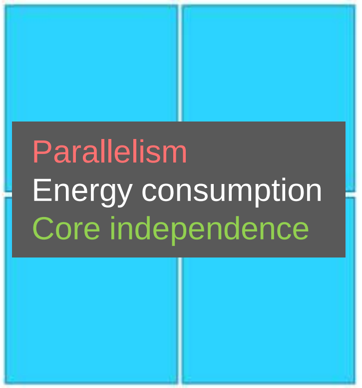
Many-Core: *Hardware accelerator with several cores called Processing Elements (PE)*





GPGPUs

Many-Core



CPUs

MSF - HSBOF on Embedded Many-Core

=> Improvement factor 6 of "Energy consumption/performance ratio" [1]

First step toward an industrial solution

Architecture	Performance	OG Rate	Energy consumption
GPGPU	94 ms	10.6 Hz	12 W
Many-core	**119 ms**	**8.4 Hz**	**0,6 W**
Multi-core	210 ms	4.7 Hz	2 W

Inria /Toyota Lexus (2 Lidars @ 25Hz)

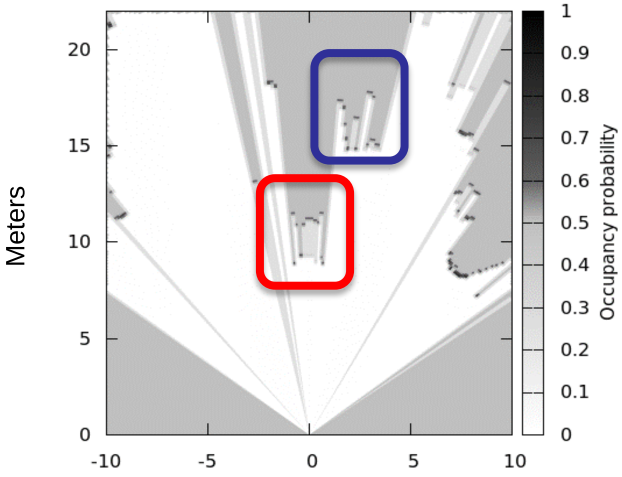
Software / Hardware Integration – µController

PhD Tiana Rakotovao

❑ MSF - HSBOF on µController *[2][3]*

⇒ *Low Cost / Energy / Size (widely used in Industrial product)*
⇒ *Implementation based on **Integer Arithmetic** (Quantized Occupancy Probability)*
⇒ *Time performance: **increase factor 5-10***
⇒ *Energy Consumption: **decrease factor 100***
⇒ ***See details in [2]***

Inria /Renault Zoé (4 Lidars @ 25Hz)



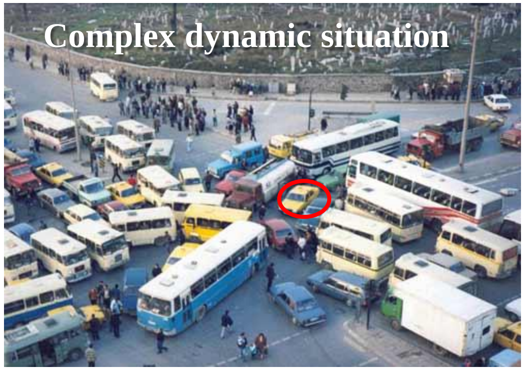
Multi-Sensor Fusion on **µController**

ARM Cortex-M3 @48MHz
- No floating-point
- Power consumption < 1Watt
- Low-cost < 2 €

[2] T. Rakotovao, et al. Multi-Sensor Fusion of Occupancy Grids based on Integer Arithmetic. IEEE ICRA 2016
[3] Patent application

Key Technology 2: Risk Assessment & Decision

=> Decision-making for avoiding Pending & Future Collisions



❑ Main difficulties

Uncertainty, Partial Knowledge, World changes, ***Human in the loop + Real time***

❑ Approach: Prediction + Risk Assessment + Bayesian Decision

- *Reasoning about* ***Uncertainty & Contextual Knowledge*** *(History & Prediction)*
- ***Avoiding Pending & Future collisions*** *(Probabilistic Collision Risk at* ***$t+\delta$****)*
- ***Decision-making*** *by taking into account the* ***Predicted behavior*** *of the observed mobile agents (cars, cycles, pedestrians …) &* ***Social / Traffic rules***

Step 1: Short-term collision risk – Outline

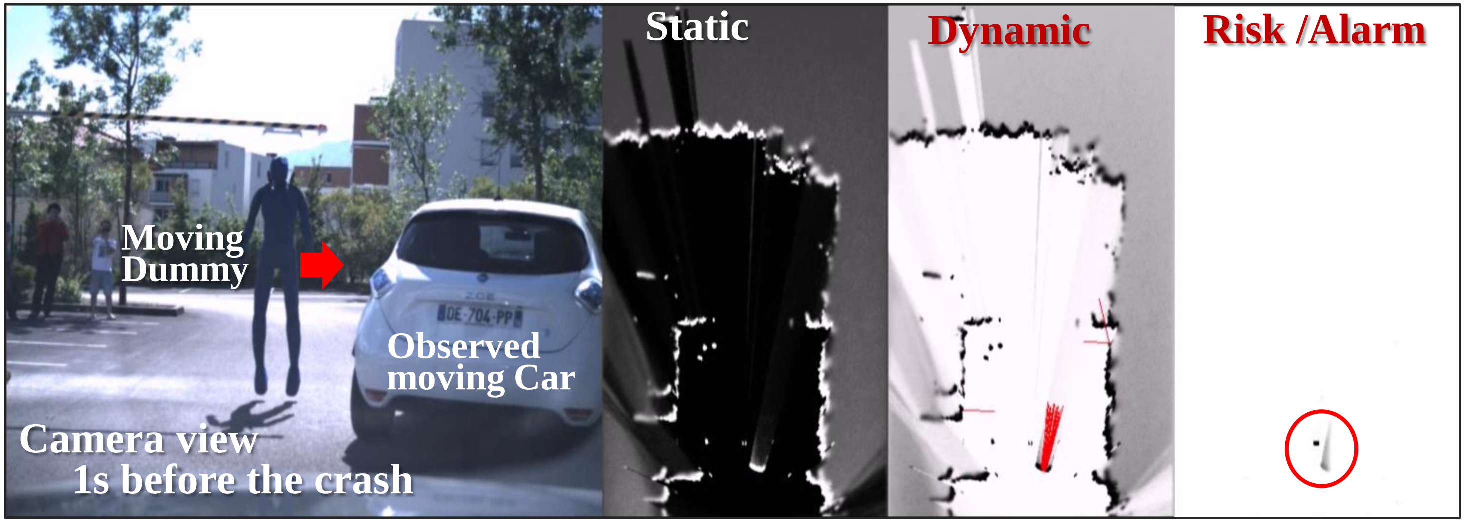
=> Grid level & Conservative motion hypotheses (proximity perception)

Objective:

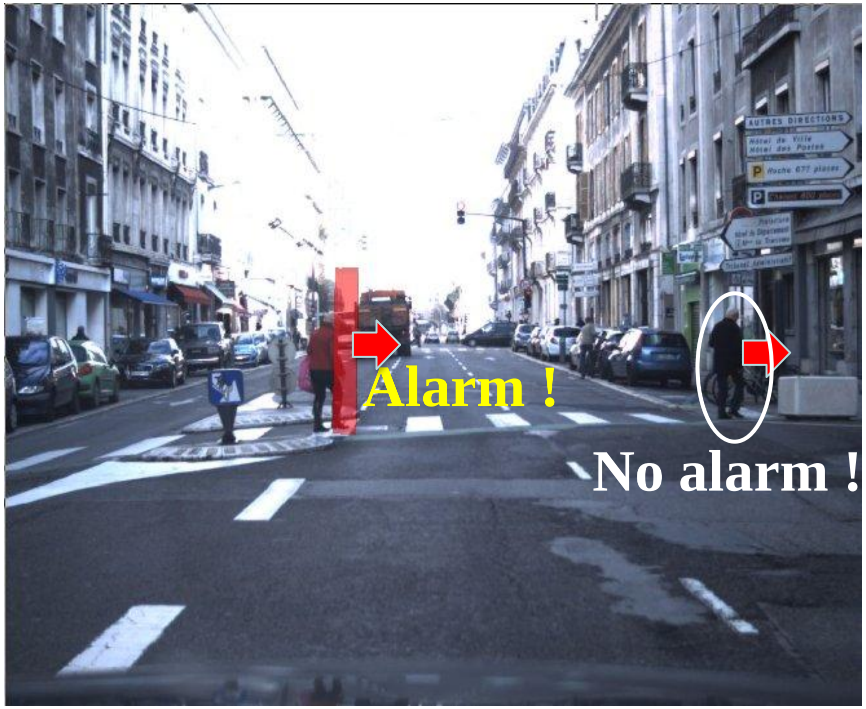
- *Detect "Risky Situations" a few seconds ahead*
- *Risky situations are localized in Space & Time*
- *Conservative motion prediction in the grid (Particles & Occupancy)*
- *Collision checking with Car model (shape & velocity) for every future time steps (horizon $t+\delta$)*

Proximity perception: d <100m and t<5s
$\delta = 0.5$ s => Precrash
$\delta = 1$ s => Collision mitigation
$\delta > 1.5$s => Warning / Emergency Braking

System outputs:



Step 1: Short-term collision risk – Experimental results



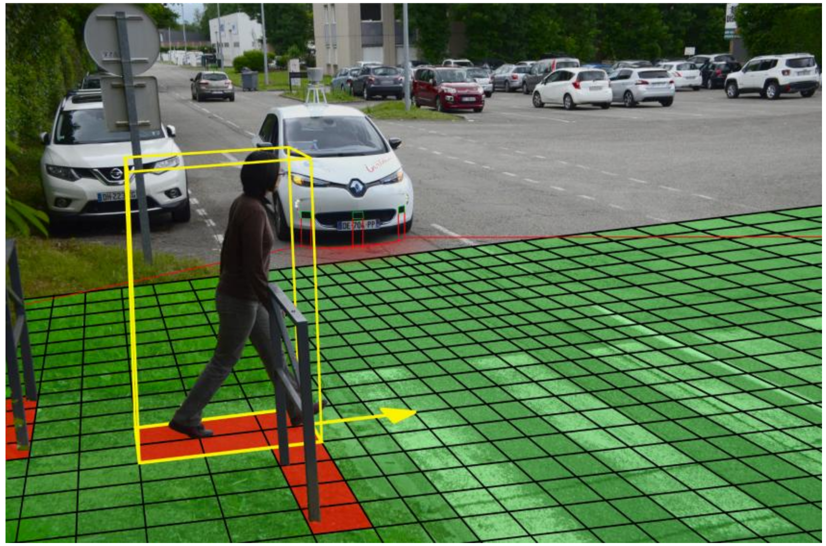
Urban street experiments

=> Almost no false alarm in complex dynamic scenes (car, pedestrians…)

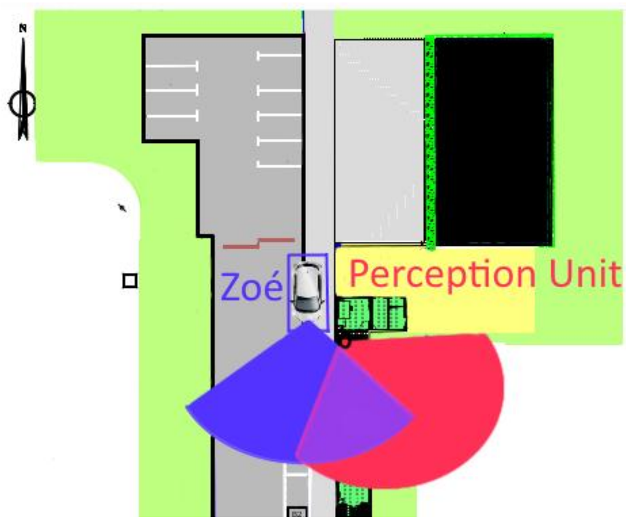
Crash scenario on test tracks

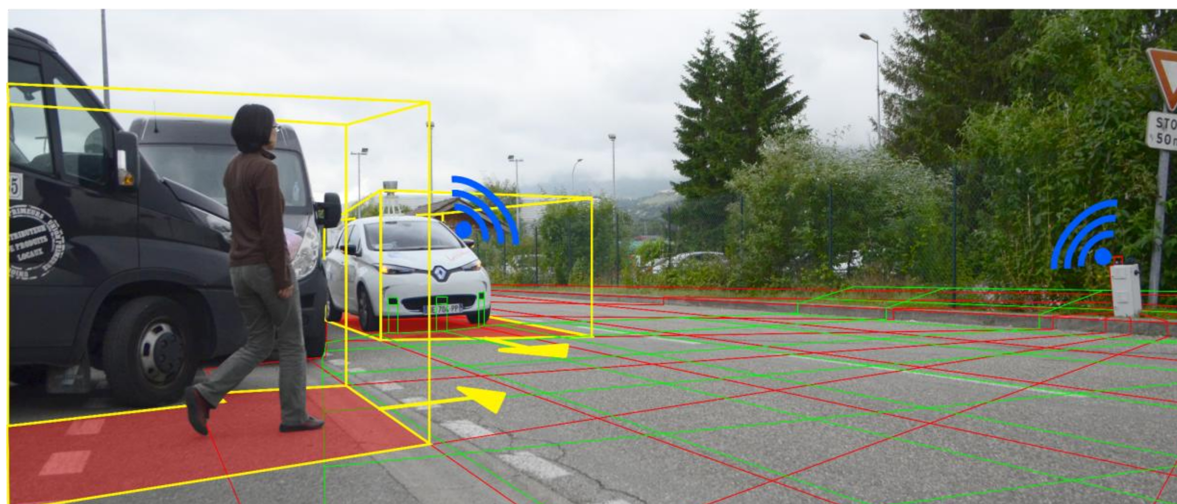
=> Almost all collisions predicted before the crash (0.5 – 2 s before)

Distributed Perception using V2X & Collision risk



Detection & Collision Risk using embedded Perception

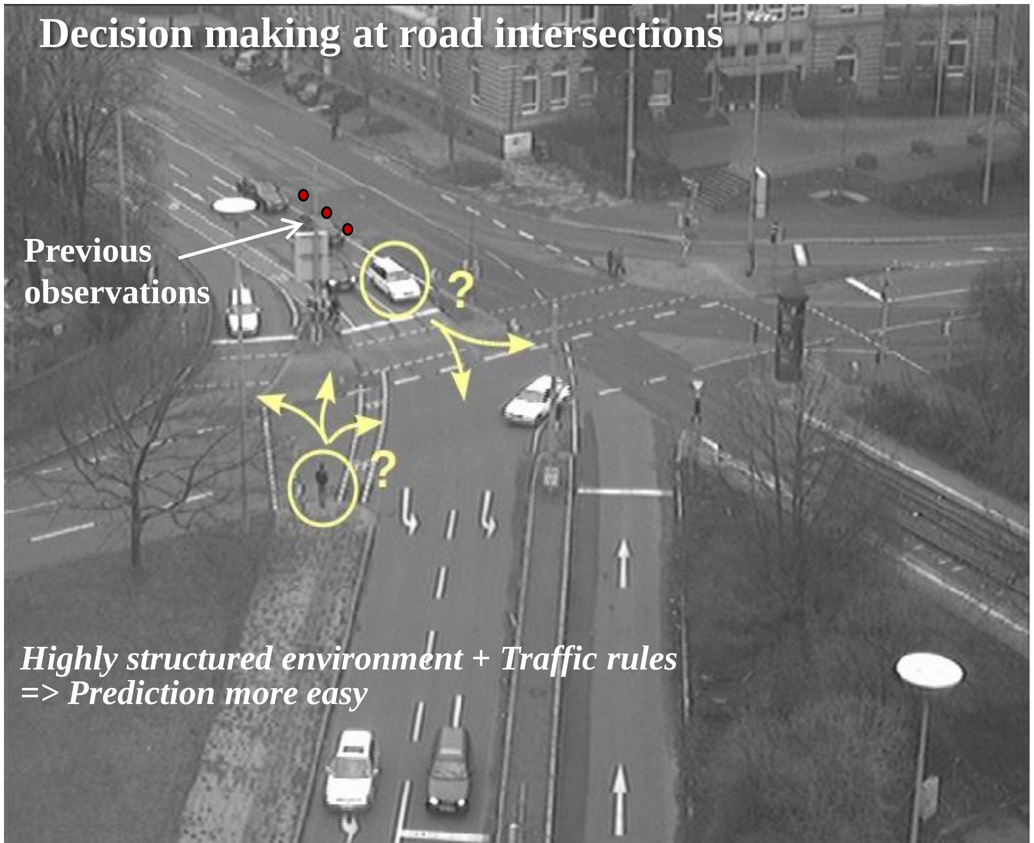


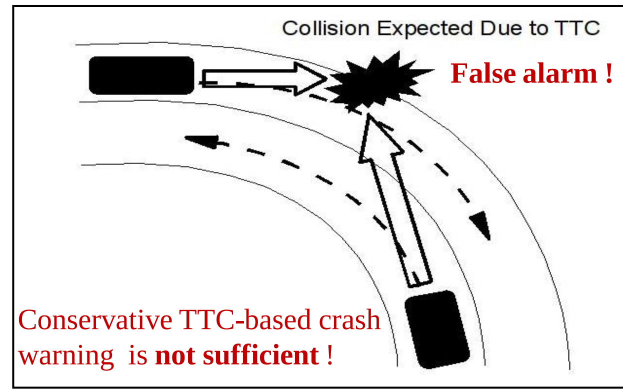


Detection & Collision Risk using Infrastructure Sensors & V2X

Step 2: Generalized Risk Assessment (Object level)
=> Increasing time horizon & complexity using **context & semantics**

⇒ Understand the **Current Situation** & its **likely Evolution** *(on a given time horizon)*
⇒ Evaluate the **Risk** of future Collision *(more complex maneuvers & trajectories)*
⇒ Highly **structured environment & Traffic rules** make **Prediction more easy**





Context & Semantics
(History + Space geometry + Traffic rules)
+
Behavior Prediction
For all surrounding traffic participants
+
Probabilistic Risk Assessment

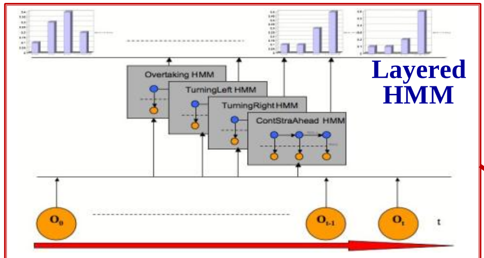
Behavior-based Collision risk *(Object level)*

Approach 1: Trajectory prediction & Collision Risk Assessment

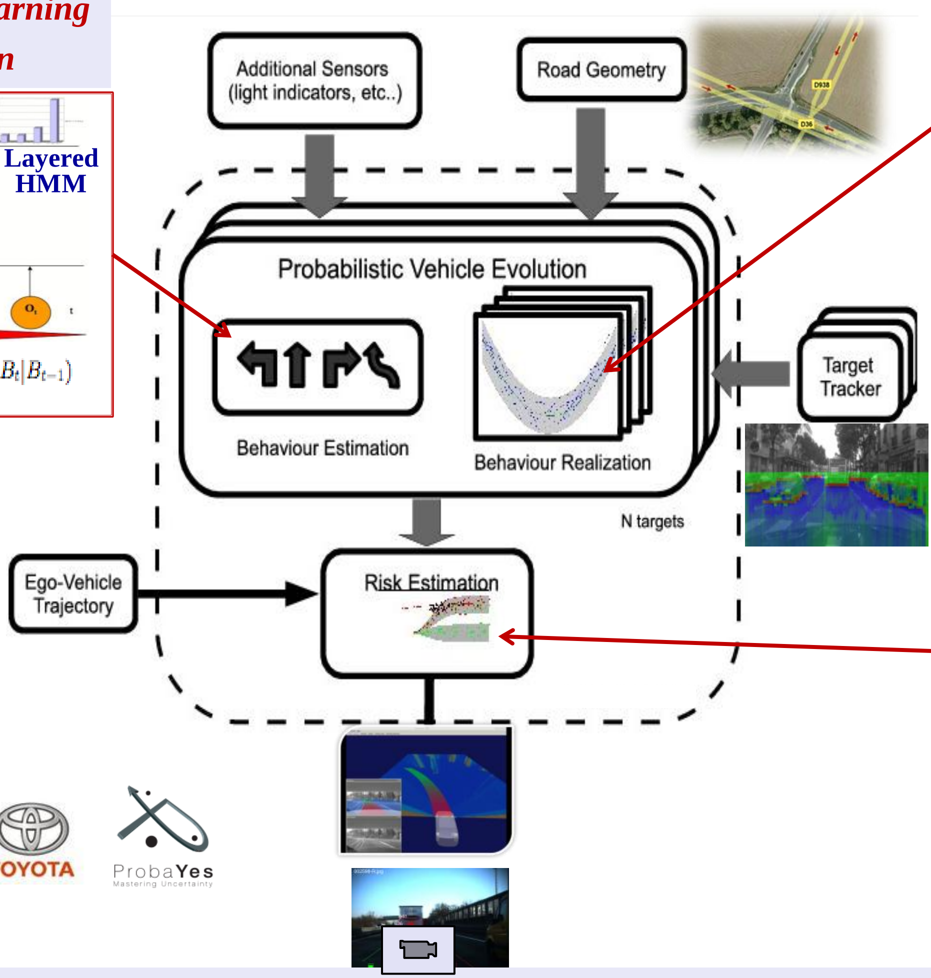
[Tay thesis 09] [Laugier et al 11]

Patent Inria & Toyota & Probayes 2010

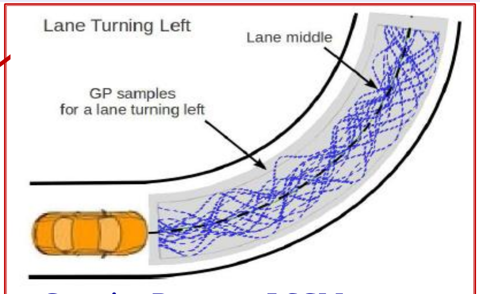
Behavior modeling & learning + Behavior Prediction



$$P(B_t|O_{1:t}) = L_{B_t}(O_{1:t}) \sum_{B_{t-1}} P(B_{t-1}) P(B_t|B_{t-1})$$

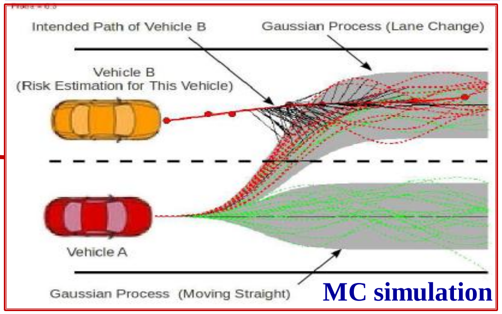


From behaviors to trajectories



Gaussian Process + LSCM

Collision risk assessment
(Probabilistic)



MC simulation

Experimental results
Behavior prediction & Risk Assessment on highways
Probayes & Inria & Toyota

Behavior-based Collision risk *(Object level)*

Approach 2: Intention & Expectation comparison

*=> Complex scenarios with **interdependent behaviors** & **human drivers***

[Lefevre thesis 13] [Lefevre & Laugier IV'12, Best student paper]

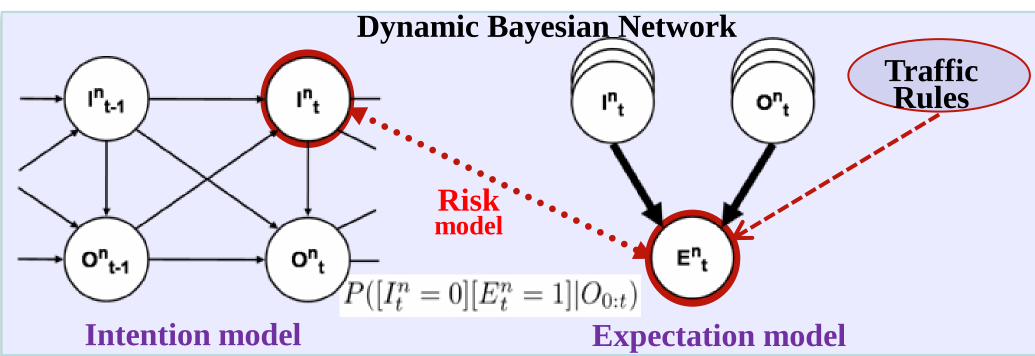
Patent Inria & Renault 2012 *(risk assessment at road intersection)*
Patent Inria & Berkeley 2013 *(postponing decisions for safer results)*

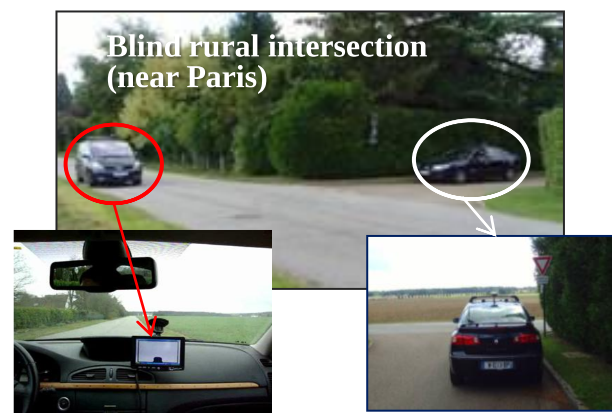
A Human-like reasoning paradigm *=> Detect Drivers Errors & Colliding behaviors*

- ✓ *Estimating **"Drivers Intentions"** from Vehicles States Observations (X Y θ S TS) => Perception or V2V*
- ✓ *Inferring **"Behaviors Expectations"** from Drivers Intentions & Traffic rules*
- ✓ ***Risk** = Comparing Maneuvers **Intention & Expectation***

*=> Taking **traffic context** into account (Topology, Geometry, Priority rules, Vehicles states)*

*=> **Digital map** obtained using "Open Street Map"*

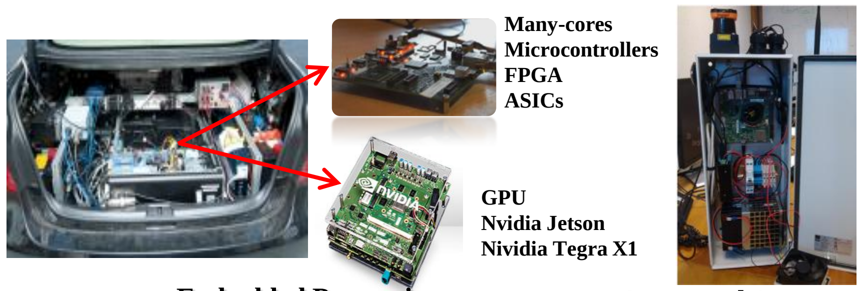




Current & Future work

❑ Approaches for Software & Hardware integration *(Embedded Perception)*

=> Reduce drastically Size, Weight, Energy consumption, Cost ... while improving Efficiency



Embedded Perception
Miniaturization & Improvements

Connected Sensor Box

CPU (2006) GPU (2010) Many-cores & GPU low power (2015)

Improved Bayesian algorithms
Integration on Lightweight Hw (2016-17)

Dedicated Hw / Sw
integration (2018-20)

Coop. CEA & IRT Nanoelec (common projects & PhD student)

❑ Technologies for Intelligent Mobility *(Perception + Decision + Control + Learning)*

- ✓ *Learning driving skills & Autonomous Driving (2 PhD)=> Berkeley & Renault + Toyota (2015-17)*
- ✓ *Human-Aware mobility in crowded environments (PhD) => ANR Valet + PIA Valeo (2016-18)*
- ✓ *Certification of Embedded Perception Systems (Postdoc) => EU ENABLE-S3 (2016-19)*
- ✓ *Connected Sensors & Lightweight Hw for Mobile Systems (PhD + Postdoc) => IRT nanoelec (2016-17)*

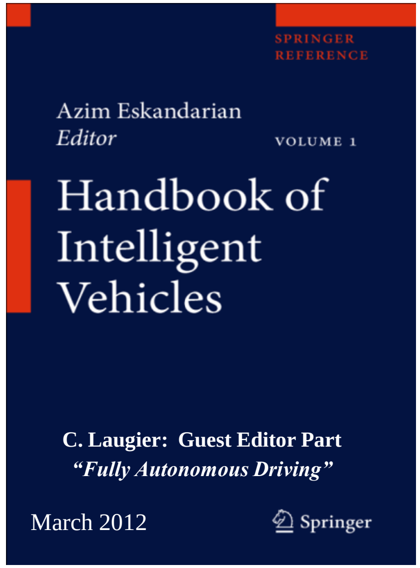
ADAS & Autonomous vehicles

Connected Infrastructure

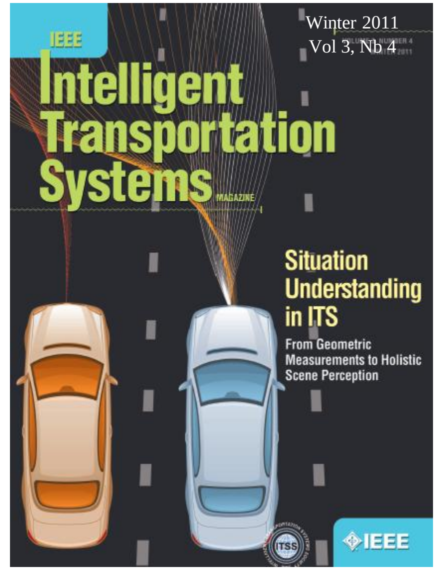
People Movers (Cybercars)

Mobile Robots (Assistance, Service, Industry)

2nd edition (*June 2016*)
Significant contribution from Inria
C. Laugier Guest co-author for IV Chapter



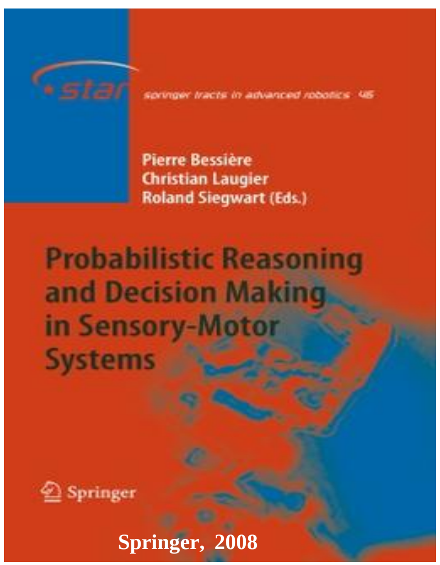
C. Laugier: Guest Editor Part
"Fully Autonomous Driving"
March 2012



Winter 2011
Vol 3, Nb 4

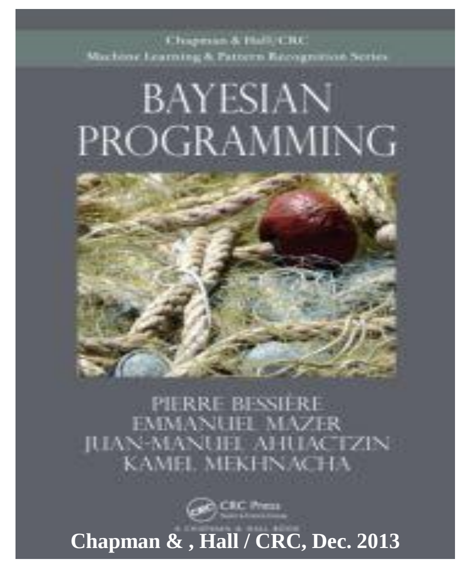
July 2013
Guest Editors:
C. Laugier & J. Machan

Thank You Any questions ?



Springer, 2008

IEEE RAS Technical Committee on "AGV & ITS"
Numerous Workshops & Special issues since 2002



Chapman & , Hall / CRC, Dec. 2013

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